University of Alberta

Library Release Form

Name of Author: Balbina Mora Garcia

Title of Thesis: Estimating Technical and Allocative Efficiency Using a Stochastic Translog Cost Function: The Case of Small and Medium-Scale Mexican Corn Producers

Degree: Master of Agriculture

Year this Degree Granted: 2004

Circuito del Sol Oriente 3905, Dep. D
Conjunto Nuevo Amanecer-Las Animas
Puebla, Pue., 72400
Mexico

Date July 28, 2004

University of Alberta

Estimating Technical and Allocative Efficiency Using a Stochastic Translog Cost Function: The Case of Small and Medium-Scale Mexican Corn Producers

by

Balbina Mora Garcia

A paper submitted to the Department of Rural Economy in partial fulfillment of the requirements for the degree of Master of Agriculture

in

Agricultural Economics

Department of Rural Economy

Edmonton, Alberta

2004

University of Alberta

Faculty of Graduate Studies and Research

The undersigned certify that they have read, and recommend to the Department of Rural Economy for acceptance, a paper entitled Estimating Technical and Allocative Efficiency Using a Stochastic Translog Cost Function: The Case of Small and Medium-Scale Mexican Corn Producers submitted by Balbina Mora Garcia in partial fulfillment of the requirements for the degree of Master of Agriculture in Agricultural Economics.

Dr. Scott R. Jeffrey
Supervisor

Dr. Terry Veeman

Date January 28, 2004

Abstract

This paper examines the question of whether access to formal credit affects efficiency of corn producers in Mexico. A two-stage analysis was used to identify the relevant socio-economic variables that have an impact on efficiency. The first stage consists of the estimation of a stochastic translog cost function that allows the decomposition of allocative and technical efficiencies. The levels of technical efficiency are then regressed against socio-economic factors such as education, age, experience and access to formal credit. The results show that education and age are significant variables affecting production decisions. Access to formal credit is not statistically significant in this analysis. Low levels of allocative and technical efficiencies are also found.

Table of Contents

List of Figures

List of Tables

Introduction

Agriculture continues to play a significant role in the economy of Mexico. In 2000, the sector accounted for approximately 6.1 per cent of Gross Domestic Product and employed almost 16 percent of the economically active population (*INEGI*). In particular, poor rural households derive most of their income from agriculture. Improving productivity in the sector is, therefore, of considerable importance in promoting economic growth and alleviating poverty in the country.

Efficiency is a very important factor of productivity growth especially in developing economies like Mexico, where resources are insufficient and opportunities for developing and adopting better technologies are dwindling. In this sense, efficiency studies are useful in showing the potential for of raising productivity through improving efficiency without increasing the resource base or developing new technologies. Estimates on the extent of efficiency can also help influence policy makers in terms of whether to focus on improving efficiency or developing new technologies in raising agricultural productivity.

The goal of this study is to examine the significance of access to formal credit as one of the major factors that influence levels of farm production and efficiency. A better understanding of this factor, which might be associated with the inability of farmers to attain the technically efficient frontier, should aid policy makers in creating improved

efficiency enhancing policies. In this study, farm efficiency is measured using a stochastic cost frontier of Mexican corn farms. The cost frontier is estimated using data from a national survey conducted for the year 2000-01. Farm efficiency is measured in terms of technical and allocative efficiencies.

The study is organized as follows: the first part involves developments in estimating stochastic cost functions; the second part discusses the situation of Mexican corn producers and a presentation of the model. The succeeding section contains the results and analysis and in the last part some conclusions are drawn from the results.

Literature Review

Producer performance can be measured in terms of economic efficiency related to cost, revenue and profit. Economic efficiency can be decomposed into technical and allocative parts. According to Farrell (1957), technical efficiency and allocative efficiency determine the total efficiency of a firm. Technical efficiency is the ability of a firm to maximize its output given a set of inputs. Allocative efficiency is the ability of a firm to use the inputs in optimal proportions given their respective prices and the production technology.

Frontier functions are used to measure economic efficiency and are estimated through techniques of parametric and non-parametric methods. Parametric methods involve the econometric estimation of parametric functions such as least-squares models (deterministic models) and stochastic frontiers. Non-parametric methods do not involve econometric estimation, but instead make use of mathematical programming. This is referred to as Data Envelopment Analysis (DEA) (e.g. Caputo and Lynch, 1993; Chavas and Aliber, 1993; Thomas and Tauer, 1994). The great advantage of this approach is that no explicit functional form is imposed on the data. However, it does not consider statistical noise. The econometric approach imposes an explicit functional form on the data and takes into account statistical noise.

Winsten (1957) first proposed deterministic frontiers[1]. In these models, all deviation from the production frontier is attributed to technical inefficiency. They do not make allowance for the effect of random shocks that might influence output (positively or negatively). Technology parameters are estimated by ordinary least-squares (OLS). The downward bias in the estimated OLS intercept is corrected by shifting it up until all corrected residuals are nonpositive and at least one is zero (e.g. Aigner and Chu, 1968; Afriat, 1972; Richmond, 1974; Ali and Chaudhry, 1990).

Aigner, Lovell and Schmidt (1977), Meeusen and van den Broeck (1977) and Battese and Corra (1977) first proposed the stochastic econometric approach using a parametric representation of technology along with a two-part composed error term. One component of the composed error term represents statistical noise and is generally assumed to follow a normal distribution. The other part represents inefficiency and is assumed to follow a particular one-sided distribution. Aigner, Lovell and Schmidt (1977) employed half-normal distributions for one-sided distribution. Stevenson (1980) employed the truncated normal and Greene (1990) proposed the two-parameter Gamma.

Production frontier functions are employed to measure technical efficiency, using an output-oriented approach. The output-oriented approach indicates how output could be expanded given the input levels. In contrast, the input-oriented approach considers how

[1] These studies often refer to production function frontiers but can also hold for cost frontiers.

inputs may be reduced relative to a desired output level. This approach is used to estimate cost efficiency. The main differences between these two approaches are:

a) The estimation of technical efficiency requires information on inputs and outputs, while the estimation of cost efficiency requires information on input prices, output quantities, total expenditure, and depending on the model, input quantities or input cost share (e.g. Battese and Coelli, 1995; Battese, 1992; Rusell and Young, 1983).

b) The estimation of technical efficiency does not impose a behavioral objective on producers, while the estimation of cost efficiency does; specifically cost minimization behavior.

Some studies have claimed that production functions are not the best approach for measuring efficiencies because farmers face different prices and endowments (Ali and Flinn, 1989). In contrast, the input-oriented approach assumes that input prices and output quantities are exogenous. Producers try to allocate inputs so as to minimize the cost of producing a given output (i.e., inputs are determined endogenously). While in certain situations, the objective of a producer is assumed to be cost minimization; in other circumstances producers may be assumed to maximize profits. In this case, input and output prices are exogenous and producers try to allocate inputs and outputs so as to maximize profit (i.e., inputs and outputs are determined endogenously).

In general, technical efficiency is a physical notion that can be measured without price information and without imposing a behavioral objective on producers. Cost and profit efficiencies are economic concepts whose measurement requires price information and the imposition of an appropriate behavioral objective on producers.

A cost frontier model can be estimated using a single-equation model or a cost system model. In the case of a single-equation model, one can calculate estimates of the parameters describing the structure of the cost frontier and producer-specific estimates of cost efficiency. Alternatively when input quantity data or input cost share data are available and applying Shephard's lemma, a cost frontier can be estimated as a component of a simultaneous-equation model. In this case, one can calculate estimates of the parameters describing the structure of the cost frontier, producer-specific estimates of cost efficiency and producer-specific estimates of cost of technical efficiency and cost of input allocative efficiency. Christensen and Greene (1976) estimated a flexible translog cost and input cost share equation system.

The use of a cost system approach entails a critical problem; how to build the relationship between the two-sided disturbances on the input share equations with the nonnegative allocative inefficiency disturbance in the cost equation (Greene 1980). This dilemma is called the "Greene problem". To solve the Greene problem, alternative approaches have been proposed:

a) To determine the analytic relationship among the allocative inefficiency disturbances and the disturbance in the cost equation. Schmidt and Lovell (1979) worked on this approach as well as Kumbhakar (1989). This approach can only be applied when restrictive functional forms are imposed, such as the Cobb-Douglas or other self-dual forms.

b) To determine the relationship through an approximation function. In this case, the known structure is imposed a priori (Schmidt 1984).

c) To disregard the relationship among the disturbances in the cost and input share equations (Greene 1980).

d) Kumbhakar (1997) proposed a model using a translog cost function that established an exact relationship between allocative inefficiency in the cost share equations and in the cost function.

In several studies, predicted efficiency indices have been regressed against a number of socio-economic characteristics in an attempt to explain the observed differences in efficiency among farms, using a two-stage procedure (Bravo-Ureta and Evenson, 1994). The first stage involves the estimation of the stochastic frontier function and the prediction of inefficiency effects, where inefficiency effects are identically distributed with one-sided error terms. The second stage involves the specification of a regression

model for predicted inefficiency effect that is opposite to the assumption of an identically distributed one-sided error term in the stochastic frontier. The inefficiency effects would only be identically distributed if the coefficients of the farm specific factors were simultaneously equal to zero. Battese and Coelli (1995) solved this problem; they estimated farm specific efficiency scores and the factors explaining efficiency differentials among farmers in a single stage estimation procedure. In this approach the technical inefficiency effects are specified in the stochastic frontier model and assumed to be independently but not identically distributed non-negative random variables.

The previous models can be estimated using cross-sectional data or panel data; however, Schmidt and Sickles (1984) identified that cross-sectional stochastic frontier models face the following issues:

a) Maximum likelihood estimation and the separation of technical inefficiency from statistical noise require strong distributional assumption on each error component. The robustness of inferences from these assumptions is not well documented.

b) Maximum likelihood estimation requires that the technical inefficiency error component be independent of the regressors.

c) The technical efficiency of producers can be estimated using the JLMS technique[2], but it cannot be estimated consistently, since the variance of the conditional mean or the conditional mode for each individual producer does not go to zero as the size of the cross section increases.

Each of these limitations is evaded with panel data since panel data allow adapting techniques that do not require strong distributional assumptions. Repeated observations of producers could be a substitute for the independence assumption and the technical efficiency of each producer can be estimated consistently as N tends to infinite, N being the number of observations on each producer.

Among models using panel data, there are two alternative approaches. In some models technical efficiency is allowed to vary across producers, but is assumed to be constant through time for each producer (time-invariant models). In other cases efficiency is allowed to vary across producers and through time for each producer (time-variant models).

The simplest panel data model is a fixed-effect model. This model assumes that random effects (v_i) are uncorrelated with the regressors. There is no distributional assumption on the inefficient components (u_i) and these are allowed to be correlated with the regressors

---

[2] Jondrow et al. (1982) proposed that the mean or the mode of the conditional distribution [$u_i(v_i-u_i)$] provides estimates of the technical inefficiency of each producer in the sample.

or with the random effects (v_{it}). Since the inefficient components (u_i) are treated as fixed (i.e. nonrandom effects), they become producer-specific intercept parameters to be estimated along with the β_ns. The model can be estimated by applying OLS (Greene 1993). However the fixed-effect model has disadvantages. The u_i also capture the effects of all factors that vary across producers but that are time invariant for each producer. This confounding of variation in technical efficiency with variation in other effects occurs whether or not the other effects are included as regressors in the model.

On the other hand, the random-effect model assumes that the u_i are randomly distributed with constant mean and variance, but are assumed to be uncorrelated with the regressors and with the v_{it}. There is no distributional assumption on the u_i, although it is required that they be nonnegative. The v_{it} have zero expectation and constant variance. This modification allows time-invariant regressors to be included in the model. This random-effect model fits into the one-way error components model in the panel data literature, and can be estimated using the two-step generalized least squares (GLS) method (Greene 1993).

The maximum likelihood estimation of a stochastic frontier panel data model with time-invariant technical efficiency is structurally similar to the procedure applied to cross-sectional data. This technique is extensively used in empirical analysis (e.g. Kumbhakar, 1990; Battese and Coelli, 1992).

Gong and Sickle (1989), based on a series of Monte Carlo experiments, found that the three approaches generate similar estimates of efficiency, in terms of correlation and rank correlation. Therefore, depending on the circumstances, one might have a preference for the fixed-effect model because of its computational ease and the lack of need for strong assumptions.

Regarding to the impact of credit programs on efficiency, several studies have analyzed this problem. O'Neill and Matthews (2003) estimated a single stage model (Battese and Coelli, 1995) to analyze the impact of debt on efficiency. They estimated a stochastic translog production function incorporating the possibility of non-neutral technological change and time invariant and time variant technical inefficiency. Unbalanced panel data from Irish farms were employed to calculate efficiency scores. They found that a higher debt ratio was negatively associated with inefficiency; that is farms which were borrowing were better managers.

Brummer and Loy (2000) studied the impact of farm credit programs in northern Germany. They estimated a stochastic translog production function, where the distribution of the non-negative u's were related to explanatory variables such as age of the farm manager, a dummy variable to identify access to credit, and others. Unbalanced panel data were employed to estimate this model, which allowed for time-varying inefficiency. It was estimated using a single stage approach as Battese and Coelli (1995).

They found that the credit program seemed to have failed to increase the competitiveness of farms.

Taylor, Drummond and Gomes (1986) analyzed the effectiveness of subsidized credit programs in Brazil. They first estimated a stochastic Cobb-Douglas production frontier and later derived the corresponding dual cost function to estimate technical and allocative efficiency. In this case, the disturbances were assumed to be independent and identically distributed as gamma random variables according to the model developed by Greene (1980). Cross-sectional data were employed. They found that credit programs did not have any effect on technical efficiency and had a slightly negative effect on allocative efficiency.

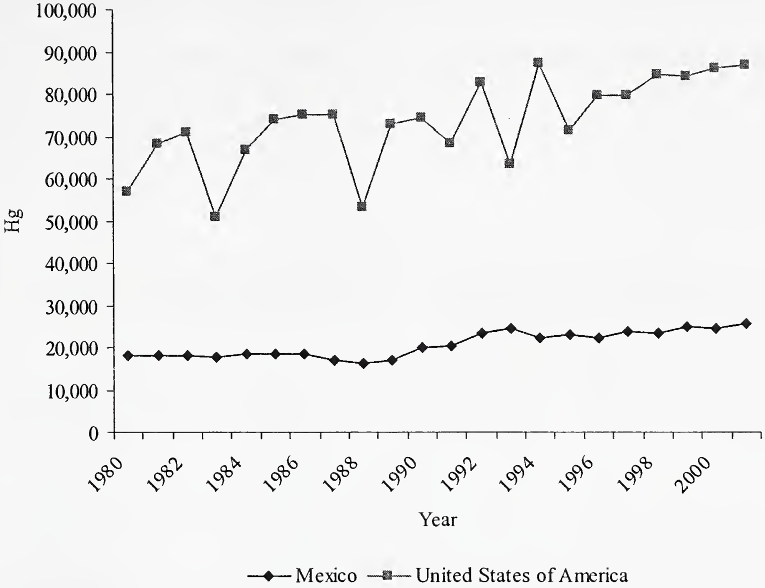
Mexican Farms' Challenge

Corn is the most important agricultural product in Mexico. Its production covers approximately 70 per cent of total arable land in Mexico. This crop has been produced in Mexico since the sixteenth century, yet the production process has not changed significantly. The government of Mexico has implemented several programs to modernize its production, such as the implementation of irrigation systems, the use of improved seeds and the substitution of capital for labour, but success in terms of efficiency has been limited because Mexican production is strongly linked to culture and limited by technical and economic factors such as the size of farms, credit, technical assistance, etc.

Figure 1 shows that basically, the corn yield per hectare in Mexico has not changed in the last twenty-two years. It has been fluctuating around 20,000 hectograms per hectare. In contrast, the United States yield increased from 57,118 to 86,722 hectograms over the same time period.

The size of farms in Mexico is one of the major obstacles in modernizing corn production. In some states, the average size of farms is three hectares or less. This size does not allow farms to be profitable. Table 1 shows the size of farms of the main producer states.

Figure 1
Corn Yield per Hectare, Mexico and U.S. (hectograms/hectare)



Source: FAO Database.

Because of the size of farms, two systems of production in Mexico can be distinguished, production for subsistence and production for trading. Production for subsistence is developed in small farms and its output is destined for consumption by peasants. This output represented approximately 5 million tons in 1997 (i.e., 25 per cent of total production). The use of family labour and transference of resources (outside income obtained by members of the family developing other activities) characterize this production. As the priority of this system is to feed the family, the quality of the corn is fundamental because it has to be good enough to be transformed according to gastronomic issues (taste, consistency, etc.). This situation has allowed the permanency

of very old types of corn (sixteenth century) and also has prevented peasants from developing their production process because they do not accept new varieties of corn. The surplus of this production is sold or exchanged for other products such as beans, pumpkins, etc.

Table 1
Average Farm Size of Main Corn Producer States in Mexico

State	National Corn Output %	Estimated Size of Corn Farms Has.
Sinaloa	15.2	21
Edo. Mexico	12.8	3
Jalisco	11.5	11
Chiapas	8.2	7
Michoacan	6.1	8
Puebla	4.8	3
Guanajuato	3.1	6
Others	38.3	-
Total	100.0	-

Source: *Fideicomisos Instituidos en Relacion con la Agricultural (FIRA).*

Conversely corn output for trading is used to satisfy the commercial demand for corn. This production represented approximately 15 million tons in 1997 (i.e., 75 per cent of total production). This system of production is based on the use of capital, irrigated systems and utilization of different types of seeds according to environmental conditions. Low costs of production, economies of scale, and inadequate means of commercialization characterize this production process. The ways of commercialization employed by these

farmers are not optimal because Mexican market structure is not well articulated and producers are forced to sell their production to intermediaries. This situation prevents farmers from trading their production in favorable conditions. Instead, they have to hastily sell it, in order to pay their loans on time and start new production (FIRA 2000).

Due to the low yield of corn production and an increasing population (1.6 per cent increase per year), corn imports have increased. In 1983 and 1994, the import growth rates were 1,166 per cent and 1,204 per cent, respectively.

The implementation of the North America Free Trade Agreement (NAFTA) is making the situation worse. Its impact on Mexican agriculture has been overwhelming especially for basic grains, which Canada and the United States can produce at a lower cost than Mexico. Corn in the United States can be produced at roughly 40 per cent of the cost of production in Mexico (Chowdhury and Allen, 2003).

In 1995, the Food and Agriculture Organization of the United Nations (FAO) carried out a two-year macroeconomic study of the implications of NAFTA in Mexico over the next 15 years. FAO conducted a survey over an area of some 7.8 million hectares of irrigated and non-irrigated cropland and found that in approximately 30 per cent of this area, the production was not economically viable; that is, the costs of production were not being covered by the sale of the produce. In general, the study showed that in 70 percent of the

land, the production costs were so high that producers were not able to compete in international markets.

According to NAFTA, by the year 2008 there will be no restrictions for trading corn between Canada, the United States of America and Mexico. Therefore Mexican farms will need to improve their performance to be able to compete with Canadian and American farms. In response, the Mexican government has designed a group of policies to achieve this goal. Among these policies, credit plays an important role since through it the Mexican government is attempting to modernize the production of this crop.

Until the mid-1990s, agricultural credit programs were characterized by subsidized interest rates, exoneration of guarantees, constitution of public funds to absorb losses due to natural disasters and public insurance systems. However, these measures did not work adequately because the Mexican financial system was underdeveloped (most of the farmers did not have access to credit) and was highly segmented, i.e. certain financial institutions only served certain farmers. As a consequence of these weaknesses, most of the credit was assigned to successful farms and the allocation of credit was based on political reasons rather than financial and economical reasons subsequently, the Mexican government changed its policies and focused on:

a) strengthening public financial institutions and eliminating subsidies;

b) the promotion of new financial institutions such as credit unions, financial leasing companies, and others;

c) facilitating the implementation of credit risk management mechanisms (hedge and insurance);

d) promoting the participation of commercial banks in agricultural credit through a system of guarantees. In the case of default, a development bank pays to the commercial bank a portion of the principal and interest. The portion paid depends on the terms of the contract, but could be up to 90 per cent. The historical rate of default in guarantees is roughly 2.9% (Acevedo, 2002).

e) the design of new financial services to satisfy specific needs of farmers;

f) modernization of prudential regulations and strengthened supervision based on accepted international practices; and

g) providing integrated support to medium and small farms (managerial information, training, technical assistance, etc.).

h) public agricultural institutions were specialized: small farms with very low yields and high levels of risk were attended by *Fondos de Solidaridad de Apoyo a la Produccion* (*PRONASOL*), which financed micro loans at zero interest rate. Low-income farms but potentially profitable were attended by *Banco Nacional de Credito Rural* (*Banrural*). In this case, real interest rates were positive, but lower than commercial bank rates. In 2001, its credit portfolio accounted for approximately U.S.$ 2,825 million, close to 26 per cent of total agricultural credit in Mexico (Acevedo, 2002).

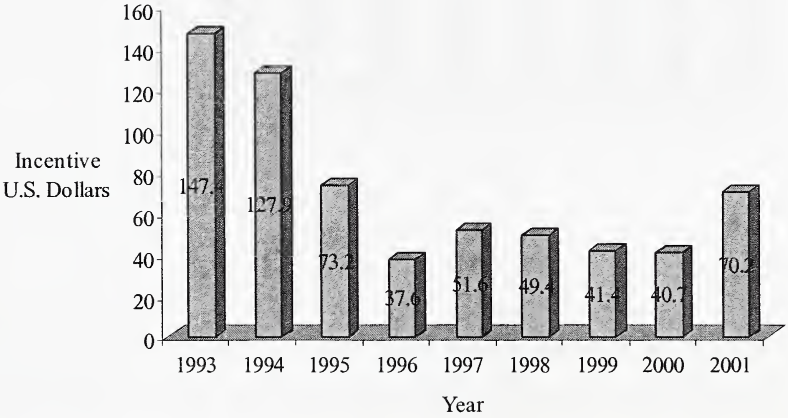
The institution in charge of the public agricultural financial system is *Fideicomisos Instituidos en Relacion con la Agricultura* (*FIRA*). This institution belongs to the central bank of Mexico. FIRA channels its funds mainly through commercial banks, Banrural and non-banking financial intermediaries. In 2001, its credit portfolio accounted for US$3,476 million, close to 32 per cent of the total agricultural credit in Mexico (Acevedo 2002). FIRA also provides technical assistance such as validation of new production processes, promotion and exhibitions of new technologies, as well as training courses for their use.

To satisfy the demand for credits below US$10,000, FIRA has implemented a system of incentives for commercial banks. The incentive consists of a payment for each loan that a bank provides. This payment intends to cover the fixed costs of banks. Since the beginning of this program (1993) until now, this incentive has allowed more than

700,000 clients to borrow funds, close to 50 per cent of the current portfolio of FIRA. Figure 2 shows the cost of this incentive over time.

Figure 2

Costs of Incentives

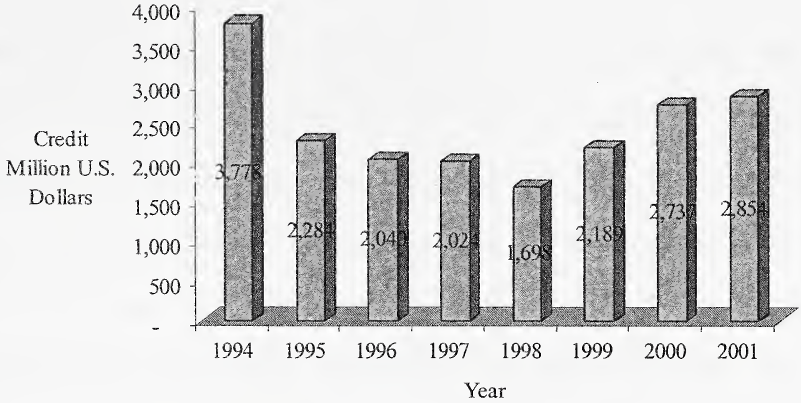


Source: BID

Another important factor that has helped to expand credit among farmers is the creation of non-banking financial institutions. These institutions started to work with FIRA in 1994. They have shown a growth rate of 23.5 per cent per year and represented 15 per cent of the portfolio of FIRA in 2001 (Acevedo, 2002). Credit unions (56) represented 3.6 per cent of the portfolio (36,000 producers). Figure 3 shows the evolution of credit provided by these institutions.

Figure 3

Credit of Non-Banking Institutions



Source: BID

According to these data, the new credit policy has been successful in terms of attending a major number of farms, but the main question is if improved access to credit has resulted in improved performance for Mexican farms.

Methodology

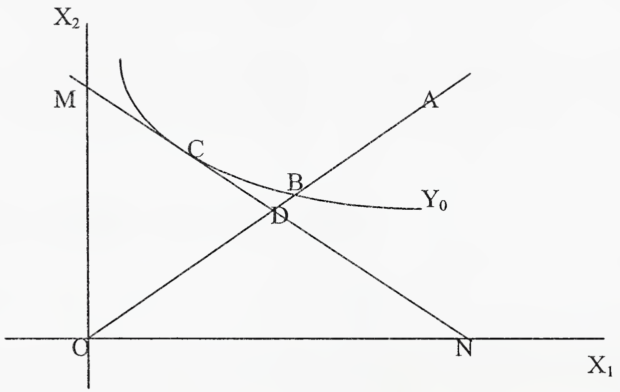
The analysis is performed in two stages. In the first stage, a translog cost frontier where factors under the control of farmers (discretionary inputs) are included as inputs in computing efficiency scores. In the second stage, efficiency scores obtained are regressed on socioeconomic attributes beyond the control of farmers (nondiscretionary inputs). The econometric estimation of the translog cost frontier is performed through a system of equations with error terms decomposed as measures of white noise, technical and allocative efficiencies[3].

According to Farrell (1957), a cost-minimizing firm does not produce a given level of output at a minimum possible cost when technical and allocative inefficiencies are presented. Figure 4 shows that a firm is producing a given level of output (Y^*) using an input combination defined by point A. The same level of output could have been produced by contracting the use of both inputs back to point B, which lies on the isoquant associated with the minimum level of inputs required to produce (Y^*). The level of technical efficiency (TE) of A is defined by the ratio 0B/0A. However, the least-cost combination of inputs that produces (Y^*) is given by point C, the point where the marginal rate of technical substitution is equal to the input price ratio w_2/w_1 where w_1 and w_2 are unit prices for X_1 and X_2 respectively. To achieve the same level of cost as at C,

[3] The model developed is based on the efficiency decomposition approach presented by Kumbhakar (1991).

the inputs could need to be radially contracted to point D. The cost efficiency or economic efficiency (CE) is defined by 0D/0A. The input allocative efficiency (AE) for A is given by CE/TE or 0D/0B.

Figure 4
Efficiency Measures
(Input-Orientation)



Based on these definitions, a cost system that allows for cost inefficiency is defined as

$$\ln C = \ln C^* + \varepsilon$$

$$\varepsilon = \ln C_t + \ln C_a + \ln C_u$$

$$S_i = S_i^* + U_i, \qquad \text{i = 1,....n}$$

where,

lnC = the natural log of total cost

lnC* = the natural log of minimum cost

ε = disturbance on the cost equation

$\ln C_t$ = technical inefficiency

$\ln C_a$ = allocative inefficiency

$\ln C_u$ = white noise

$\ln C_a$ and $\ln C_t$ = nonnegative since technical and allocative inefficiencies increase cost

S_i = actual share

S_i^* = the optimal share of input i in the total cost

U_i = disturbance on the input share equation (a mixture of allocative inefficiency and white noise)

$\sum U_i = 0$ (since cost shares must sum to unity)

A significant issue in estimating this system is how to model the relationship between the disturbances on the input share equations (U_i) with the nonnegative allocative inefficiency disturbance on the cost equation ($\ln C_a$). In this study, the specification model proposed by Kumbhakar (1991), an extension of Schmidt's (1984) model is use; that is,

$$\ln C_a = U'AU$$

where,

A = pre-specified matrix

$U=(U_1,U_2 \ldots U_n)$

The cost function in terms of a translog cost function is

$$\ln C = \ln C^* + \varepsilon$$

$$\ln C = \alpha + \beta_i \sum_{i=1}^{n} \ln w_i + \frac{1}{2}\beta_{ij} \sum_{i=1}^{n} \ln w_i \ln w_j + \delta_1 \ln y + \frac{1}{2}\delta_2 \ln y^2 + \lambda_i \sum_{i=1}^{n} \ln w_i \ln y + \ln C_t + \ln C_a + \ln C_u$$

where,

w_i = input prices

y = output

α, βi, δi, λi = parameters to be estimated

$$\sum_{i=1}^{n} \beta_i = 1$$

$$\sum_{i=1}^{n} \beta_{ij} = \sum_{j=1}^{n} \beta_{ji} = 0$$

$$\sum \lambda_i = 0$$

With these restrictions, the function becomes linearly homogeneous in input prices.

Applying Shephard's lemma:

$$S_i = S_i^* + U_i,$$

$$S_i = \beta_i + \sum_{j=1}^{n} \beta_{ij} \ln w_j + \lambda_i \ln y, + \partial \ln C_a / \partial \ln w_i \qquad \text{i=1,...n}$$

Therefore $\partial \ln C_a / \partial \ln w_i = U_i$ and considering that $\sum_{i=1}^{n} U_i = 0$,

one can rewrite the relationship as

$\ln C_a = u'ku$

where,

$u=(U_1, U_2 \ldots, U_{n-1})'$

k = (n-1) x(n-1) matrix, its elements are well defined functions of the elements of A

$$U_i = \partial(u'ku)/\partial \ln w_i \quad \text{if} \quad \sum_{j=1}^{n-1} k_{ij}\beta_{ij} = -\frac{1}{2}, \quad \sum_{j=1}^{n-1} k_{lj}\beta_{ij} = 0 \quad \text{for all } i \neq l \qquad i=1,\ldots n-1$$

In matrix notation, $kB_0 = -\frac{1}{2}I$ thus $k = -\frac{1}{2}B_0^{-1}$

where K is a positive definite matrix.

Considering that the only constraint is that k must be a positive definite matrix, the identity matrix is employed.

$$\ln C_a = -\frac{1}{2}u' B_0^{-1} u$$

In this model, it is assumed that output is exogenous and inputs are endogenous; therefore the share equations do not contain technical inefficiency.

Thus, the system of equations is as follows:

$$\ln C = \alpha + \beta_i \sum_{i=1}^{n} \ln w_i + \frac{1}{2} \beta_{ij} \sum_{i=1}^{n} \ln w_i \ln w_j + \delta_1 \ln y + \frac{1}{2} \delta_2 \ln y^2 + \lambda_i \sum_{i=1}^{n} \ln w_i \ln y + \varepsilon$$

$$\varepsilon = \ln C_t + \ln C_a + \ln C_u$$

$$S_i = \beta_i + \sum_{j=1}^{n} \beta_{ij} \ln w_j + \lambda_i \ln y, + U_i$$

$$\ln C_a = -\frac{1}{2} u' B_0^{-1} u$$

where,

i) u is distributed independently and identically over firms as multivariate normal with zero mean and constant covariance Σ,

ii) $\ln C_u$ is i.i.d $N(0, \sigma_u^2)$,

iii) $\ln C_t$ is i.i.d. $N(0, \sigma_t^2)$ truncated at zero from below

iv) $\ln C_u$, $\ln C_t$ and u are assumed to be mutually independent.

The joint probability density function is:

$$f(\varepsilon, u) = f(u) f(\varepsilon \setminus u)$$

where,

$$f(u) = \frac{1}{(2\pi)^{(n-1/2)} \mid \Sigma \mid^{1/2}} \exp\left\{ -\frac{1}{2} u' \Sigma^{-1} u \right\}$$

$$f(\varepsilon \setminus u) = f(\ln C_t + \ln C_u)$$

$$f(\ln C_t + \ln C_u) = \frac{2}{(\sigma_u^2 + \sigma_t^2)^{1/2}} \frac{1}{(2\pi)^{1/2} \Phi(\mu / \sigma)} \exp\left\{ -\frac{z^2}{2(\sigma_u^2 + \sigma_t^2)} \right\}$$

$$\sigma = \frac{\sigma_u \sigma_t}{(\sigma_u^2 + \sigma_t^2)^{1/2}}$$

$$\mu = \frac{z\sigma_t^2}{(\sigma_u^2 + \sigma_t^2)}$$

$\Phi =$ the cumulative probability density function (pdf) of a standard normal variable

$$z = \varepsilon - \ln C_a$$

The log-likelihood function is

$$L = \ln f(u) + \ln f(\varepsilon \setminus u)$$

$$L = const - \frac{1}{2} \ln \mid \Sigma \mid - \frac{1}{2} (u' \Sigma^{-1} u) + \ln \sigma - \ln \sigma_u - \ln \sigma_t - \ln \Phi(\frac{\mu}{\sigma}) - \frac{z^2}{2(\sigma_u^2 + \sigma_t^2)}$$

where,

The (i,j) th element of Σ, is $\sigma_{ij} = \frac{1}{F}\sum_{f} u_{if}u_{jf} = \frac{1}{F}\sum (S_{if} - S_{if}^{*})(S_{jf} - S_{if}^{*})$

F= number of firms

Allocative inefficiency is computed using the following formula:

$$\ln C_{a} = -\frac{1}{2}u' B_{0}^{-1} u$$

Technical inefficiency is computed as follows

$$\ln C_{t} = \mu + \sigma \frac{\phi(\frac{\mu}{\sigma})}{\Phi(\frac{\mu}{\sigma})}$$

where,

$\phi(\frac{\mu}{\sigma})$ is the pdf of a standard normal variable

Since by assumption, socio-economic attributes are beyond the control of farmers a second stage process is conducted. In this regression model technical efficiency is expressed as a function of socioeconomic attributes such as age, experience, education, and access to formal credit.

Empirical Results

The data used in this study are a heterogeneous sample from a national survey of corn producers for the agricultural year 2000-2001. The survey was conducted by a Mexican bank. The sample is comprised of 58 small and medium size peasant farms. In Mexico, most of the small farmers own less than 5 hectares of land and operate under inferior conditions. These conditions can be described by poor quality rain-fed soil, as well as little or no access to technology, credit, storage facilities and marketing channels. These farmers depend on what they produce for household consumption. They also sell a portion of their corn production and hire out their labour services to other farms, in order to supplement household income needs. In contrast, medium farmers have moderate profit margins and have some capacity to respond to changes in the market. They operate in better conditions than small farmers do. These farmers do not only produce for their own consumption but also for local and regional markets. They often have better access to technology and credit than smaller farms.

The data contain information on quantities and costs of inputs and production. Four inputs (labour -L-, fertilizers –F-, seeds –S-, and capital -K- that compromises miscellaneous expenses) were defined; their summary statistics are listed in Table 2, together with values for corn production (y). The inputs are measured in Mexican pesos terms (American dollar/Mexican peso roughly equal to 0.09).

Table 2

Summary Statistics of Inputs and Production

	Mean	St. deviation	Minimum	Maximum
Production (ton/ha)	4.7	1.9	0.5	8.0
Total cost	4,693	1,861	990	8269
Price of labour	47.3	16.7	10.5	120.0
Price of fertilizers	5.8	7.1	0.6	21.3
Price of seeds	32.9	43.8	3.0	250.0
Price of capital	14.9	37.8	1.0	230.3
Share of labour	0.10	0.07	0.01	0.30
Share of fertilizers	0.21	0.09	0.00	0.40
Share of seeds	0.15	0.05	0.03	0.34
Share of capital	0.54	0.12	0.24	0.77

Source: The name of the Mexican bank is omitted from this paper due to confidential reasons.

From the system described in the previous sections, the share equation for capital was dropped prior to carrying out the estimation. The resulting estimates are listed in Table 3. The first order coefficients can be interpreted as cost elasticities since total cost and regressors are in natural logarithms. The cost elasticies for labour and capital are 0.05 and 0.33, respectively in the restricted model. This cost function is more sensitive to changes in seed price (0.37). The estimate of σ_t was found to be statistically significant in the model. This result is a route to test for the presence of technical inefficiency since the asymptotic "t" test rejects the hypothesis σ_t=0 in the model and the magnitude of σ_t is greater relative to σ_u.

The restrictions of linearly homogeneous in input prices on the parameters were statistically tested using the likelihood ratio (LR) test. The LR statistic is also reported in Table 3. The rest of the properties of cost functions are satisfied, except for that this function is quasi-concave instead of being concave.

Table 3

Parameter Estimates for the Stochastic Cost Function (Standard Error in Parentheses)

Variable[1/]	Unrestricted Model [2/]	Restricted Model [2/]
Constant	5.1212*	6.4526*
	(0.5011)	(0.3485)
ln(L)	0.5147	0.0451
	(0.2849)	(0.1380)
ln(F)	0.2150*	0.2598*
	(0.1036)	(0.1285)
ln(S)	0.3164*	0.3669*
	(0.0736)	(0.0563)
ln(K)	0.0945	0.3283*
	(0.1502)	(0.0965)
$\ln(L) * \ln(L) * \frac{1}{2}$	-0.1319	0.0204
	(0.0786)	(0.0422)
ln(L) * ln(F)	0.0240	0.0461
	(0.0230)	(0.0318)
ln(L)*ln (S)	-0.0039	0.0025
	(0.0264)	(0.0228)
ln(L) * ln(K)	-0.0494*	0.1286
	(0.0244)	(0.0224)
$\ln(F) * \ln(F) * \frac{1}{2}$	0.0341*	-0.0341
	(0.0160)	(0.0314)

Table 3. Extended

Variable[1/]	Unrestricted Model [2/]	Restricted Model [2/]
ln(F) * ln(S)	0.0040	-0.0376
	(0.0191)	(0.0198)
ln(F) * ln(K)	-0.0007	0.0256
	(0.0148)	(0.0139)
$\ln(S) * \ln(S) * \frac{1}{2}$	-0.0169	-0.0634*
	(0.0247)	(0.0183)
ln(S) * ln(K)	0.0563*	0.0985*
	(0.0238)	(0.0192)
$\ln(K) * \ln(K) * \frac{1}{2}$	-0.0715*	-0.0552*
	(0.0277)	(0.0155)
ln(y)	0.4992	-0.1506
	(0.3642)	(0.2397)
$\ln(y) * \ln(y) * \frac{1}{2}$	-0.0980	0.0648
	(0.1327)	(0.1004)
ln(y) * ln(L)	0.1215*	0.1286*
	(0.0583)	(0.0474)
ln(y) * ln(F)	-0.0547	-0.1441*
	(0.0421)	(0.0516)
ln(y) * ln(S)	-0.1275*	-0.1931*
	(0.0238)	(0.0110)
ln(y) * ln(K)	0.1352*	0.2087*
	(0.0611)	(0.0443)
σ_u	0.0003*	0.00008*
	(0.000008)	(0.000002)

Table 3. Extended

Variable[1/]	Unrestricted Model [2/]	Restricted Model [2/]
σ_t	0.1357*	0.1290*
	(0.0091)	(0.0093)
Log likelihood	477.70	446.17
Chi-squared test statistic Critical value at 5%		63.06 12.59

1/ In this table, L represents labour, F for fertilizers, S for seeds, K for capital and y for output.

2/ The difference between the unrestricted and restricted models is that the latter includes the imposition of linear homogeneity in input prices.

*Significant at 5%.

The estimates of allocative efficiency (AE) for each farm are listed in Table 4. Comparing across farms, the results show a wide variation. Allocative efficiency ranges from 56.4 to 74.1 per cent. The summary statistics for AE are provided in Table 5. The corn farms in the sample appear to be operating at a low level of allocative efficiency. These results suggest that Mexican corn farmers fail to fully exploit the potential of a technological advancement and make decision errors on allocation of inputs as reflected in the variation of their management capacity. These results do not conform to an important view in the literature on development economics stating that farmers practicing traditional agriculture are "poor but efficient".

Table 4

Degrees of Allocative Efficiency

Farm	Allocative Efficiency	Farm	Allocative Efficiency	Farm	Allocative Efficiency
1	0.6407	21	0.5944	41	0.6928
2	0.6060	22	0.6028	42	0.6364
3	0.6216	23	0.5777	43	0.7410
4	0.6023	24	0.5873	44	0.7074
5	0.6064	25	0.5975	45	0.7030
6	0.6779	26	0.6259	46	0.6942
7	0.7379	27	0.5876	47	0.7129
8	0.5961	28	0.6415	48	0.6981
9	0.5977	29	0.6953	49	0.7017
10	0.6075	30	0.6462	50	0.6294
11	0.6353	31	0.6018	51	0.6264
12	0.6314	32	0.6272	52	0.6124
13	0.6303	33	0.7089	53	0.5643
14	0.6289	34	0.7067	54	0.5925
15	0.5963	35	0.6488	55	0.6441
16	0.6196	36	0.6119	56	0.6632
17	0.6535	37	0.6479	57	0.7219
18	0.6323	38	0.6416	58	0.6307
19	0.6297	39	0.6053		
20	0.6025	40	0.6228		

The hypothesis of "poor but efficient" (Schultz 1964) has led policy-makers to believe that poor traditional farmers will not improve as long as they adhere to their existing

outdated production technologies. This belief has resulted in an increased emphasis on investment in generating new and more productive technologies. However, the introduction of new technologies requires management and information. Farmers in developing economies such as Mexico, with low literacy rates, poor extension services, and inadequate physical infrastructures have great difficulty in understanding new technologies. Although farmers can adjust over-time to these changes, new technologies are being generated and diffused continuously that make more difficult for farmers to adapt to changes. In general, farmers have to deal with the disequilibrium created by continuous changes in input and output prices.

Table 5
Summary Statistics of Allocative Efficiency

	Allocative Efficiency
Mean	0.64
Standard deviation	0.04
Minimum	0.56
Maximum	0.74

The estimates of technical efficiency (TE) for each of the peasant-farms under the restricted model are reported in Table 6. The results show a wide variation in TE across farms. The minimum and maximum efficiency levels are 0 and 97.7 per cent respectively. The mean of this sample is 52.6 per cent with a standard deviation of 37.9 per cent. Given the mean of 52.6 per cent, the corn farms in the sample also appear to be operating at a

low level of technical efficiency. These results also suggest that this sample of farmers could increase their technical efficiency and output through better use of available resources given the current state of technology.

Table 6

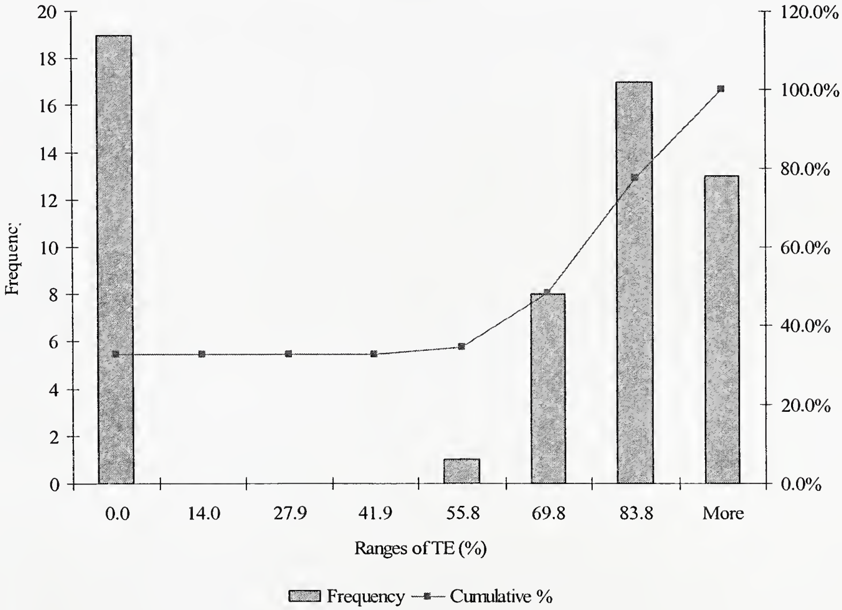
Degrees of Technical Efficiency

Farm	Technical inefficiency	Farm	Technical inefficiency	Farm	Technical inefficiency
1	0.8268	21	0.7723	41	0.6911
2	0.0000	22	0.7462	42	0.7308
3	0.0000	23	0.8563	43	0.0000
4	0.6710	24	0.9092	44	0.7138
5	0.7500	25	0.8942	45	0.0000
6	0.7955	26	0.7341	46	0.9139
7	0.0000	27	0.9328	47	0.5735
8	0.0000	28	0.7603	48	0.0000
9	0.6795	29	0.8489	49	0.7209
10	0.0000	30	0.8445	50	0.8203
11	0.0000	31	0.8888	51	0.8008
12	0.0000	32	0.0000	52	0.0000
13	0.8634	33	0.0000	53	0.7346
14	0.5082	34	0.8519	54	0.8936
15	0.7830	35	0.9772	55	0.0000
16	0.8081	36	0.0000	56	0.8655
17	0.6871	37	0.0000	57	0.7854
18	0.0000	38	0.0000	58	0.0000
19	0.8317	39	0.6897		
20	0.6871	40	0.6553		

A frequency distribution of farm vis-à-vis technical efficiency is given in Figure 5. The graph shows that technical efficiency varies widely, however 32.8 and 29.3 per cent of the observations are concentrated in 0 and 83.8 per cent respectively. The farmers exhibiting zero degree of technical efficiency might be operating close to subsistence level and they therefore prefer an inferior outcome that is relatively certain to the prospect of a higher average return with a greater level of risk attached.

Figure 5

Distribution of the Degrees of Technical Efficiency

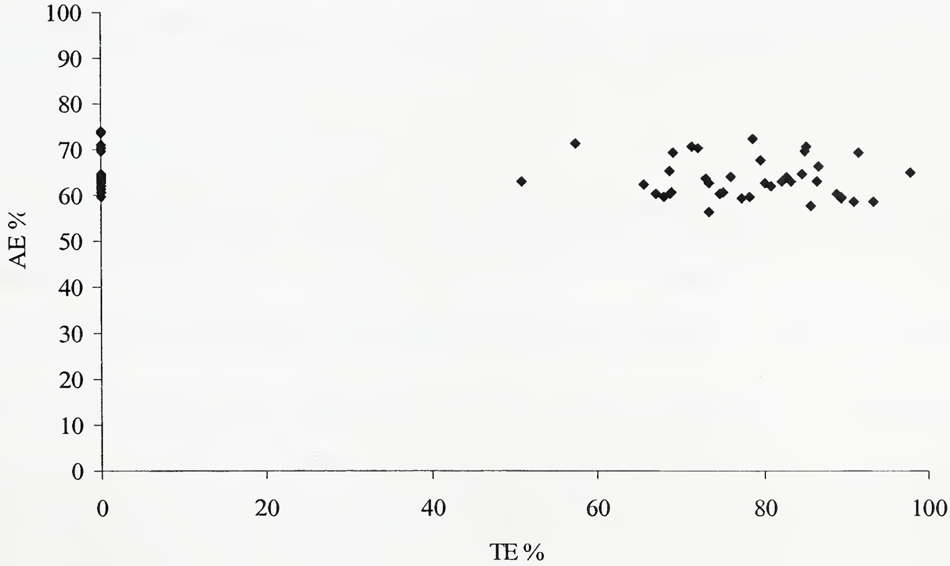


The high production gap that exists among these farmers suggests the need to strengthen the existing agricultural extension services. These estimates are useful in the sense that

they provide information for policy makers for dissemination of agricultural information, and, to some extent, the reduction of risk in using new technologies.

Figure 6 shows a comparison between these two types of inefficiencies. In general, the farms that could be considered technically efficient (above 90.0 per cent) are operating under low levels of allocative efficiency. In this range, the best allocative efficiency farm (69.4 per cent) is 91.4 per cent technical efficiency.

Figure 6
Technical Efficiency vs. Allocative Efficiency



Impact of Socio-Economic Variables on Technical Efficiency

Despite the tendency in the efficiency literature to conduct one-stage procedure, two-stage procedure was chosen for the study because it was assumed that socioeconomic attributes are beyond the control of farmers -nondiscretionary inputs- (Ray, 1988). The measures of technical efficiency obtained were related to various explanatory variables using data from 58 peasant-farms. One of the important features of Mexican agriculture is that farmers often produce only at subsistence level, enough to meet their family needs instead of producing for market profits. This forces farmers to produce below the production frontier. Inefficiency can arise from socio-economic, demographic or environmental characteristics.

The socio-economic characteristics that were considered in this model were 1) education, measured in number of years of schooling completed by the household head, 2) age of the household head, 3) experience, years that the household head has worked in agriculture (there is a negative weak association between age and experience, its correlation coefficient is -0.004) and 4) credit, equal to 1 for farmers that reported receiving credit and zero otherwise. The summary statistics of these variables are listed in Table 7.

Table 7

Summary Statistics of Socio-Economic Factors

	Mean	Standard Deviation	Minimum	Maximum	Count
Education (years in school)	4	4	1	16	58
Age (number of years)	45	13	21	67	58
Experience (number of years)	10	10	1	45	58
Credit (dummy = 1 with credit dummy = 0 otherwise)					37

Source: The name of the bank is omitted due to confidential reasons.

Two approaches can be taken to determine the relationships between technical efficiency and socio-economic factors, considering the lower bound of zero on the dependent variable. One could use maximum likelihood estimates of a logit probability function to determine the probability that a farm is technically efficient. The dependent variable is therefore defined as a binary efficiency measure where the variable equals one if the farm is fully efficient and zero otherwise. The dependent variable is then regressed against the socio-economic variables defined. The alternative approach is to use a Tobit regression (censored regression) to predict the actual level of efficiency given the independent factors. In this case, a Tobit regression was used due to it assumes the data are truncated above or below certain values and it is not necessary to redefine the dependent variable. Table 8 lists the estimates and their Wald chi-square statistics.

Table 8

Parameter Estimates for the Tobit Regression

Variable	Coefficient	Wald chi-square statistic	The 95% critical value from $\chi^2_{(1)}$
Constant	-0.4953	3.20	3.84
Education	0.0766	21.64	3.84
Age	0.0134	7.10	3.84
Experience	-0.0042	0.49	3.84
Credit	-0.0162	0.37	3.84
σ^2	0.1661		
N	58		
Log-likelihood function	-36.06		

In terms of socio-economic farm characteristics, technical efficiency is found to increase with education and age. The estimated coefficient sign is consistent with the hypothesis that efficiency increases with education. Education, which represents human capital of the household head, has a positive impact on efficiency since educated farmers are able to perceive changes, to understand the available information, to draw conclusions from it and consequently to reallocate resources in response to these changes in economic conditions. There is no expected sign for age since it incorporates the two opposing effects of experience and aging. While older farmers are expected to have greater inefficiencies because they are less adaptable to new technological developments, more experienced farmers are expected to achieve higher levels of technical efficiency. In this case, the effect of experience seems to dominate.

The estimated coefficient sign on the experience variable indicates that the number of years in corn farming has a negative effect on farm efficiency. This result is not consistent with the previous results; however, this variable is not significant thus its implications are not reliable.

Access to formal credit permits a farmer to enhance technical efficiency by overcoming financial constraints for the purchase of higher quality variable inputs. Thus it is expected that credit can help increase technical efficiency. In this case, the lack of significance of this variable suggests that access to formal credit is not a major constraint for these farmers.

In general, these results imply that Mexican corn farms not only need to be more efficient in their production activities but also need to be more responsive to market indicators, so that scarce resources are utilized efficiently to increase productivity as well as profitability. In this sense, Mexican policy-makers should rationalize agricultural development policies in education, technological developments, and improvements in the input-market efficiency.

Conclusions

The study attempted to examine the relationship between efficiency and access to formal credit on Mexican corn farmers. It was found that access to formal credit is not a relevant variable on improving efficiency in Mexican farms. The results also reveal a positive relationship between efficiency and various management variables such as farmer's age and education. Low levels of both allocative and technical efficiencies were found, averaging 64.0 and 52.6 per cent, respectively, which suggests that considerable scope exist for raising the income of farmers by improving their efficiency.

The results also indicate that increased investment in inputs such as equipment and fertilizer, alone is not the answer to increase corn productivity. Better management, information, and utilization of resources are as important and should be equally emphasized if any benefits are to be expected from increasing expenditure on these inputs. The consequence here is that, while credit availability may provide traditional farmers the opportunity to invest in modernize inputs, there is no guarantee that these inputs will be used in such manner as to achieve the full extent of output gains possible.

Based on these results, policy-makers should support programs that encourage the growth of agriculture through the improvement of education that makes people increase their capacity to assimilate and use information to reduce transaction costs. Education does not

necessarily mean formal education. Education may come in the form of seminars, and/or training-courses to help improve farm management skills. Improved transportation, marketing, and communications systems are also critical since lower costs for these systems can reduce transaction costs and improve information flows, and thereby facilitate broad-based agricultural growth. Agricultural research and extension to generate and facilitate the adoption of new technologies as well.

In general, the explanatory power of the model was acceptable, but there are still ways to further improve it, such as a one-stage analysis, the imposition of local concavity, the determination of size and the selection of a random sample that allows the generalization of the results to a greater proportion of Mexican corn farms. An important limitation of this model is the use of cross-sectional data. Cross-sectional models require strong distributional assumptions on each error component and the estimates are not consistent, since the variance of the conditional mean for each individual producer does not go to zero as the size of the cross section increases. Each of these limitations is evaded with the use of panel data. Aside from the benefits of improving the estimation, the use of panel data could also refine the impact of credit, since the effects of credit are reflected over time not in short run. It takes time for the implementation and learning of new technologies.

The inclusion of risk aversion analysis is also fundamental in studies for developing countries since an important number of farmers are operating close to subsistence level and they might be non-neutral to risk so their attitudes to risk do not allow them to operate at the point where the marginal value product of each input is equal to its respective marginal factor prices.

Bibliography

Acevedo, Rommel and Javier, Delgado. 2002. El Papel de los Bancos de Desarrollo Agricola en el Acceso al Credito Rural. Departamento de Desarrollo Sostenible. Banco Interamericano de Desarrollo (BID).

Afriat, S.N. 1972. “Efficiency Estimation of Production Functions.” *International Economic Review.* 13:568-98.

Aigner, D.J. and S.F. Chu. 1968. ”On Estimating the Industry Production Function.” *American Economic Review.* 58: 826-39.

Aigner, D.J., C.A.K. Lovell, and P. Schmidt. 1977. “Formulation and Estimation of Stochastic Frontier Production Function Models.” *Journal of Econometrics.* 6: 21-37.

Ali, M., and Flinn, J.C. 1989. Profit Efficiency among Basmati Rice Producers in Pakistan Punjab. *American Journal of Agricultural Economics.* 71:303-310.

Ali, M. and M.A. Chaudhry. 1990. “Inter-Regional Farm Efficiency in Pakistan’s Punjab: A Frontier Production Function Study.” *Journal of Agricultural Economics.* 41:62-74.

Battese, G.E. and G.S. Corra. 1977. "Estimation of a Production Frontier Model: With Application to the Pastoral Zone off Eastern Australia." *Australian Journal of Agricultural Economics.* 21:169-79.

Battese, G.E. 1992. "Frontier Production Functions and Technical Efficiency: A Survey of Empirical Applications in Agricultural Economics." *Agricultural Economics.* 7:185-208.

Battese, G.E. and T.J. Coelli. 1992. "Frontier Production Functions, Technical Efficiency and Panel Data: With Application to Paddy Farmers in India." *Journal of Productivity Analysis.* 3:153-69.

Battese, G.E. and T.J. Coelli. 1995. "A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data," *Empirical Economics.* 20:325-32.

Bauer, P.W. 1990. "Recent Developments in the Econometric Estimation of Frontiers." *Journal of Econometrics*. 46:39-56.

Bravo-Ureta, B.E. and R.E. Evenson. 1994. "Efficiency in Agricultural Production: The Case of Peasant Farmers in Eastern Paraguay." *Agricultural Economics*. 10:27-37.

Brummer, Bernhard and Jens-Peter, Loy. 2000. "The Technical Efficiency Impact of Farm Credit Programmes: A Case Study of Northern Germany." *Journal of Agricultural Economics*. 51:405-18

Caputo, M.R. and L. Lynch. 1993. "A Nonparametric Efficiency Analysis of California Cotton Ginning Cooperatives." *Journal of Agricultural and Resource Economics.* 18:251-65.

Chavas, J-P. and M. Aliber. 1993. "An Analysis of Economic Efficiency in Agriculture: A Nonparametric Approach." *Journal of Agricultural and Resource Economics.* 18:1-16.

Chowdhury, A.A. Farhad and J. Albert, Allen. 2003. Impact of NAFTA on U.S. Corn Trade. Selected Paper Prepared for Presentation at the Southern Agricultural Economics Association Annual Meeting, Mobile, Alabama.

Christensen, L.R. and W.H. Greene. 1976. "Economies of Scale in U.S. Electric Power Generation," *Journal of Political Economy.* 84:655-76.

Coelli, T. D.S.P. Rao and G.E. Battese. 1998. An Introduction to Efficiency and Productivity Analysis. Norwell:Kluwer.

Colin, Fraser and Sonia, Restrepo. 1996. Communication for Rural Development in Mexico: In Good Times and in Bad. FAO.

Fare, R. and C.A.K. Lovell. 1978. "Measuring the Technical Efficiency of Production." *Journal of Economic Theory*. 19: 150-62.

Farrell, M.J. 1957. "The Measurement of Productive Efficiency". *Journal of the Royal Statistical Society*. (Series A General), 120: 253-81.

Fideicomisos Instituidos en Relacion con la Agricultura (FIRA). 2000. Oportunidades de Desarrollo del Maiz Mexicano.

Gong, B.H., and R.C. Sickles. 1989. "Finite Sample Evidence on the Performance of Stochastic Frontier Models Using panel Data." *Journal of Productivity Analysis*. 1:229-61.

Greene, W.H. 1980. "Maximum Likelihood Estimation of Econometric Frontier Functions." *Journal of Econometrics*. 13:27-56.

Greene, W. H. 1990. "A Gamma-Distributed Stochastic Frontier Model." *Journal of Econometrics*. 46:141-164.

Greene, W.H. 1993. "The Econometric Approach to Efficiency Analysis." Productive Efficiency: Techniques and Applications. New York: Oxford University Press.

Green H., William. 2000. *Econometric Analysis*. New Jersey: Prentice Hall, Inc.

Instituto Nacional de Estadistica, Geografia e Informatica (INEGI). www.inegi.gob.mx.

Kopp, R. J. 1981. "The Measurement of Productive Efficiency: A Reconsideration." *Quarterly Journal of Economics*. 97: 477-503.

Kumbhakar, S. 1989. "Modeling Technical and Allocative Inefficiency in Translog Production Function." *Economics Letters*. 31:119-124.

Kumbhakar, S.C. 1990. "Production Frontiers, Panel Data, and Time-Varying Technical Inefficiency." *Journal of Econometrics*. 46:201-12.

Kumbhakar, S.C. 1991. "The Measurement and Decomposition of Cost-Inefficiency: The Translog Cost System." *Oxford Economic Papers*. 43:667-683.

Kumbhakar, S.C. 1997. "Modeling Allocative Inefficiency in a Translog Cost Function and Cost Share Equations: An Exact Relationship." *Journal of Econometrics*. 76:351-56.

Kumbhakar S.C. and C. Lovell. Stochastic Frontier Analysis. Cambridge University Press. 2000.

Meeusen, W., and J. van den Broeck. 1977. "Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error." *International Economic Review.* 18:435-44.

O'Neill, Suzanne and Alan, Mattheuws. 2003. "Technical Change and Efficiency in Irish Agriculture."

Ray, S. 1988."Data envelopment analysis, nondiscretionary inputs and efficieny: an alternative interpretation". *Socio-economic planning sciences*, 22:167-176.

Richmond, J. 1974. "Estimating the Efficiency of Production." *International Economic Review.* 15:515-21.

Russell, N.P. and T. Young. 1983. "Frontier Production Functions and the Measurement of Technical Efficiency." *Journal of Agricultural Economics*. 34:139-49.

Schmidt, P., and C.A.K. Lovell. 1979. "Estimating Technical and Allocative Inefficiency Relative to Stochastic Production and Cost Frontiers." *Journal of Econometrics.* 9:343-66.

Schmidt, P. and C.A.K. Lovell. 1980. "Estimating Stochastic Production and Cost Frontiers when Technical and Allocative Inefficiency Are Correlated." *Journal of Econometrics*. 13:83-100.

Schmidt, P. 1984. "An Error Structure for Systems of Translog Cost and Share Equations." Workshop Paper No. 8309, Department of Economics, Michigan State University, East Lansing, Mich.

Schmidt, P., and R.C. Sickles. 1984. "Production Frontiers and Panel Data." *Journal of Business and Economic Statistics*. 2:367-74.

Schultz, T.W. 1964. *Transforming Traditional Agriculture*. Yale University Press.

Stevenson, R.E. 1980. "Likelihood Functions for Generalized Stochastic Frontier Estimation." *Journal of Econometrics*. 13:57-66.

Taylor, T.G., H.E. Drummond and A.T. Gomes. 1986. "Agricultural Credit Programs and Production Efficiency: An Analysis of Traditional Farming in Southeastern Minas Gerais, Brazil." *American Journal of Agricultural Economics*. 68:110-19.

Thomas, A.C. and L.W. Tauer. 1994. "Linear Input Aggregation Bias in Nonparametric Technical Efficiency Measurement." *Canadian Journal of Agricultural Economics*. 42:77-86.

Timmer, C.P. 1971. "Using a Probabilistic Frontier Production Function to Measure Technical Efficiency". *Journal of Political Economy*. 79: 776-94.

Winsten, C.B. 1957. "Discussion on Mr. Farrell's Paper." *Journal of the Royal Statistical Society* (Series A, General), 120: 282-84.

THESIS 2004 23618
c. 1
MORA GARCIA, BALBINA (2004)
ESTIMATING TECHNICAL AND
ALLOCATIVE EFFICIENTY USING A. . .